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Big data and predictive analytics in humanitarian supply chains: Enabling visibility and coordination in the presence of swift trust

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Abstract

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Findings - Results indicate that BDPA has a significant influence on visibility and coordination. Further, results suggest that swift trust does not have an amplifying effect on the relationships between BDPA and visibility and coordination. However, the mediation test suggests that swift trust act as a mediating construct. Hence, we argue that swift-trust is not the condition for improving coordination among the actors in humanitarian supply chains.

Research limitations/implications - The major limitation of the study is that we have used cross-sectional survey data to test our research hypotheses. Following Guide and Ketokivi (2015), we present arguments on how to address the limitations of cross-sectional data or use of longitudinal data that can address common method bias (CMB) or endogeneity related problems.

Practical implications - Managers can use our framework, first, to understand how organizational resources can be used for creating BDPA and second, how BDPA can help to build swift trust and be used to improve visibility and coordination in the humanitarian supply chain.

Originality/value - This is the first research that has empirically tested the anecdotal and conceptual evidence. The findings make notable contributions to existing humanitarian supply chain literature and may be useful to managers who are contemplating the use of BDPA to improve disaster relief related activities.

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Keywords- Big data, predictive analytics, swift trust, visibility, coordination, contingent resource-based view, resource-based view, humanitarian supply chain, confirmatory factor analysis, regression analysis.

1. Introduction

Natural and human-made disasters continue to impact society. In 2013, natural disasters alone cost society more than 192 billion USD (Caulderwood, 2014). The impacts of natural disasters on human lives and properties can be partially attributed to poor management of relief efforts in the aftermath of an event (Altay, 2008; Soneye, 2014). Major losses can result from a lack of coordination among humanitarian supply chain actors, which results in inadequate response in affected areas (Noori et al. 2016).

The complexity of humanitarian supply chains has attracted serious attention from academics and practitioners (Beamon and Kotleba, 2006; Kovacs and Tatham, 2009; Kovacs and Spens, 201; Oloruntoba et al. 2017). Benini et al. (2009) argued that survivor needs assessment is the most important aspect of managing complex disaster relief efforts. However, information regarding survivor needs or alternative routes leading to affected areas is often not available (Swanson and Smith, 2013). Therefore, disaster relief teams are often unable to reach affected areas in time, making relief to survivors a difficult objective (Altay, 2008). Additionally, humanitarian supply chains are often hastily formed due to unpredictable nature of the events (Tatham and Kovacs, 2010). As a result of these factors, the design of humanitarian supply chains can be more complicated than the design of commercial supply chains.

Coordination and collaboration in humanitarian supply chains have been the subject of debate among humanitarian actors and their workers engaged in disaster relief operations (van Wassenhove, 2006; Balcik et al., 2010; Moshtari, 2016; de Camargo et al. 2017). In the literature, however, the terms coordination and collaboration are often used interchangeably. Coordination is often limited to the sharing of information and resources, whereas collaboration is usually concerned with working together to create something new (see Balakrishnan and Geunes, 2004; Tsanos et al. 2014; Raue and Wieland, 2015). Hence, in our study, we restrict our focus to coordination, vice collaboration, among actors in the humanitarian supply chain.

Akhtar et al. (2012) argue that coordination among humanitarian actors is one of the most critical factors in deciding the overall success of the disaster relief operations. Kabra and Ramesh (2015) further argue that poor coordination among humanitarian actors often increases suffering due to a resulting mismatch between demand and supply. Humanitarian supply chains must avoid duplication of resources and services, whether by filling gaps or preventing overlaps, and ensure that various organizations are synchronized to achieve a common objective, thereby enabling a more coherent, effective, and efficient response (Gillmann, 2009). Akhtar et al. (2012) further note that tangible resources (e.g., finance, technology, and people) and intangible resources (e.g., leadership, extra efforts, relevant experiences and education, relationship management skills, research abilities and performance measurement techniques) are imperative to ensure coordination among actors involved in disaster relief operations.

Following Arshinder et al. (2008) and Akhtar et al. (2012) arguments, effective and efficient coordination requires each link of the supply chain to share information and take into the account the impact its actions have on other stages. A lack of coordination is often due to conflict among the humanitarian actors resulting from information asymmetry and a lack of trust (Tatham and Kovacs, 2010; Akhtar et al. 2012; Altay and Pal, 2014). Hence, improving information visibility and accuracy can perhaps improve coordination among humanitarian supply chain actors (Akhtar et al. 2012). Research has broadly discussed the levers and barriers of coordination, thereby providing conceptual and anecdotal evidence, but there remains a paucity of research explaining how and when humanitarian actors can create effective and efficient coordination.

This study applies the contingent resource-based view (CRBV; Brush and Artz, 1999) to further our understanding of *how* and *when* humanitarian actors can create coordination. Drawing on resource-based view (RBV), we argue that organizations may achieve a desired competitive advantage through the bundling of strategic resources which are valuable, rare, inimitable and non-substitutable (Barney, 1991), while the CRBV suggests that this is dependent on specific conditions. Visibility is one of the desired capabilities in the humanitarian supply chain leveraged to reduce risk of poor coordination due to asymmetric information (Fawcett and Fawcett, 2013; Wang et al. 2017). In this study, we consider big data and predictive analytics (BDPA) as an organizational capability to improve visibility. Fawcett and Waller (2014) argue that big data is one of the forces which may shape future supply chains. Gupta and George (2016) argue that the big data may continue to remain as the next big thing for the organizations to gain competitive advantage. There is a growing stream of literature on the application of big data or technology in predicting natural disasters (Goswami et al. 2016) or used for guiding disaster relief operations (Delmonteil and Rancourt, 2017), however, it is not clear how BDPA can be effective in increasing visibility in humanitarian supply chain and enhancing coordination among the humanitarian actors. In fact, both the conceptual and empirical contributions in humanitarian operations are still fragmented, making it difficult to compare and accumulate results to draw meaningful conclusions. In this research, we focus on two important outcomes: *visibility in humanitarian supply chain* and *coordination* among humanitarian actors. Specifically, we address the first research question:

RQ1: What are the effects of BDPA on visibility and coordination in humanitarian supply chains?

Direct performance effects are often regarded as crucial, but they are not sufficient to explain the complexity of the reality (Boyd et al. 2012). Thus, scholars have acknowledged that the final effects are contingent to specific environment contexts (Sousa and Voss, 2008; Eckstein et al. 2015). This view is reflected in the contingency theory (CT) (Donaldson, 2001). Hence, to address the existing situation, we adopt contingency theory to examine the specific context wherein the impact of BDPA on visibility and coordination remains effective.

Swift trust has been recognized as a key area of managerial concern (Tatham and Kovacs, 2010) which may enhance visibility in humanitarian supply chains and improve the level of coordination among humanitarian actors. Swift trust is regarded as one of the key constructs, but the existing works thereby providing conceptual and anecdotal evidence, little rigorous empirical tests exists of such benefits. Specifically, we address our second research question:

RQ2: What are the effects, if any, of swift trust on the relationship between BDPA, visibility, and coordination?

In answering these questions, we add to the understanding of the links between BDPA and visibility/coordination and the interaction effect of swift trust on the links between BDPA and visibility/coordination, thus contributing to the growing humanitarian operations and BDPA literature. From practitioner view, we provide theory focused and empirically tested guidance for managers to understand the application of BDPA in improving visibility in humanitarian supply chain and improving coordination among humanitarian actors.

The rest of the paper is organized as follows. The next section presents the theoretical framing. The third section focuses on the theoretical framework and hypotheses development. In the fourth section, we have outlined the research design, providing detailed discussion related to survey instrument design, pretesting, data collection procedure and non-response bias. The fifth section presents our data analyses. The sixth section of the paper highlights our findings, research contributions and the managerial implications of the study. Finally, we provide conclusions to our study.

2. Conceptual Background

2.1 Resource Based View (RBV) of the firm

Taylor and Taylor (2009) argue that RBV is one of the most popular organizational theories since Barney's (1991) seminal contribution. Some scholars (e.g. Esper and Crook, 2014; Hitt et al., 2016) in recent years have argued that the RBV can explain a variety of firm and supply chain outcomes. Barney (1991) suggests that RBV may help an organization examine its competitive advantage, thus offering immense guidance to organizations for optimal utilization of strategic resources. Akter et al. (2017) argue that BDPA can be considered a dynamic capability –an extension of RBV (Teece et al. 1997)– that results from the firm's ability to reconfigure firm-level and supply-chain level resources. Augier and Teece (2009) have argued that when dynamic capabilities enable organizations to achieve coordination, they benefit from complementarities and better decision making (Augier and Teece, 2009; Gupta and George, 2016; Akter et al. 2016). Gupta and George (2016) have explained how basic, human, and intangible firm resources can be used efficiently and effectively to create BDPA capability, which has the potential to be an important antecedent to visibility in a humanitarian supply chain and coordination among humanitarian actors.

2.2 Need for Contingent Resource Based View (CRBV)

Despite of the popularity of RBV, it has attracted criticisms from various scholars that the theory suffers from context insensitivity. For example, Ling-yee (2007) argues that RBV is unable to identify the conditions in which resources or capabilities may be useful. CT addresses this notion of contingent conditions and argues that internal and external conditions may influence supply chain design (Aragon-Correa and Sharma, 2003; Grotsch et al. 2013). Conditions may also influence the selection of resources or capabilities needed to drive desired performance under diverse conditions. Simply put, CT suggests organizations must adapt to the environmental conditions in which they exist (Eckstein et al., 2015).

2.3 Big Data

The term "big data" is often used to describe massive, complex, real-time unstructured, semi-structured and structured data which requires sophisticated management, analytical, and processing techniques to draw meaningful insights (Fosso Wamba et al., 2015; Gupta and George, 2016). However, there is a lack of consensus on the definition of big data and their characteristics. Initially, big data were characterized using 3V's (i.e. volume, velocity and variety). Over the years, other characteristics like veracity and value were added (see Fosso Wamba et al., 2015) and the trend continues to include further characteristics. However, the volume, velocity and variety are important characteristics which constitute the foundation of the big data.

2.4 Toward the conceptualization of a big data & predictive analytics (BDPA) capability

The empirical research focusing on BDPA is limited. However, recently scholars have acknowledged that BDPA is an organizational capability which may be exploited by organizations to gain competitive advantage (Gupta and George, 2016; Akter et al., 2016; Fosso Wamba et al., 2017). Organizational capabilities are defined as a higher-order construct which relies on bundling of strategic resources (Brandon-Jones et al. 2014). Sirmon et al. (2011) argue that the capabilities which are essential for the organization need to be identified on the basis of existing environmental conditions under which the organization is functioning. Hence, the effective exploitation of these capabilities may help to understand how organizations achieve and sustain competitive advantage.

Brandon-Jones et al. (2014) argue that resources and capabilities can be exploited together. For example, Akter et al. (2016) examine the effect that resources and BDPA capability have on organizational performance. Ravichandran et al. (2005) consider how information systems resources and capabilities are an important source of competitive advantage. They find that information systems (IS) capabilities are necessary for an organization to utilize relevant technological, human, and relational sources. Hitt et al. (2001) argue that exploitation of human capital resources may lead to improved performance; however, the human capital alone and its interplay with other capabilities may sometimes increase costs. Hence, it is necessary to build capabilities to exploit existing resources. Next, following the research of Gupta and George (2016), we suggest that the resources required for developing BDPA capability are comprised of tangible resources, human capital, and intangible resources.

2.5 Tangible Resources

According to RBV logic (see Barney, 1991), tangible resources are those that can be sold or bought in the market. Examples include financial assets and physical assets of the firm. These resources are readily available to all firms and are unlikely to provide any competitive advantage on their own. That said, tangible resources (defined below for this study) may be utilized efficiently and effectively to create distinct capabilities.

2.5.1 Basic resources

Gupta and George (2016) argue that besides data and technology, organizations need to invest money and time into their big data initiatives. Since BDPA is relatively new in comparison to other capabilities, most organizations have yet to explore the financial and time-based requirements to implement it. In such cases, organizations may not yield desired results in a timely manner. Hence, we consider financial investments and time as two basic resources that are important for building BDPA capability.

2.5.2 Data

In recent years, scholars have acknowledged that besides land, labor, machine, capital and materials, data is also considered as one of the important factors of production (Gupta and George, 2016). In the past, organizations heavily relied on structured data to make important decisions. However, the volume and variety of data have increased significantly due to rapid advancements in technology. Gupta and George (2016) identify five sources of data: public data, private data, data exhaust, community data, and self-quantification data. Hence, these data have immense information which can be exploited to build BDPA.

2.5.3 Technology

Zhu and Kraemer (2002) argue that an organization's information and communications technology (ICT) infrastructure is considered an important resource. ICTs are critical resources that enable humanitarian organizations to assist local populations and host governments. Thus, following the logic of RBV of the organization, we argue that use of such strategic resources as ICTs may lead to competitive advantage (Barney, 1991). ICTs are key elements of the global response to disasters and armed conflict scenarios (Wentz, 2006). Asplund et al. (2008) argue that emerging information infrastructures play a critical role in improving cooperation among actors in humanitarian operations.

2.6 Human Resources

Gupta and George (2016) argue on the basis of Hitt et al. (2001) and Barney (1991) that human resources consist of employee's experience, knowledge, business acumen, problem-solving abilities, leadership qualities and relationships with others. Hence, on the basis of previous IT capabilities research, these skills can be broadly classified into technical skills and managerial skills, which could be important in the exploitation of BDPA in humanitarian operations (Bhardwaj, 2000; Ravichandran et al., 2005; Dubey and Gunasekaran, 2015; Gupta and George, 2016).

2.6.1 Technical skills

Technical skills refer to the know-how required to use new forms of technology to extract intelligence from big data. Gupta and George (2016) argue that some of these skills include competencies in machine learning, data extraction, data cleaning, statistical analysis, and understanding programming paradigms such as MapReduce.

2.6.2 Managerial skills

Managerial skills, unlike technical skills, are often acquired through long years of working in same or different departments (Gupta and George, 2016). Within the context of a firm's big data function, the intelligence gathered from the data may be of no use if the managers fail to understand the context in which the gathered insights can be useful. Hence, the ability to predict market behavior is an essential quality which data analysts should possess. Secondly, interpersonal skills and the ability to develop swift trust may be critical to the successful use of BDPA in humanitarian supply chains, in that such soft skills can be seen as valuable, rare, inimitable and non-substitutable (Mata et al., 1995; Kearns and Lederer, 2003).

2.7 Intangible Resources

Of the three type of organizational resources classified by (Grant, 1991), intangible resources are often considered central to organizational performance, especially in dynamic situations (Teece et al., 1997). However, unlike tangible resources, intangible resources do not have clear and visible boundaries, and their value is highly context-dependent (Barney, 2014; Teece, 2014). Hence, intangible resources are not tradeable in the market like most of the tangible resources and most intangible resources are valuable, rare, inimitable, and non-substitutable (Barney, 1991). This suggests that intangible resources are highly heterogeneous (Teece, 1991). Hence, following Gupta and George (2016), we argue that BDPA and organizational learning are heterogeneous across firms, and we describe some intangible resources below that may contribute to building BDPA capability.

2.7.1 Organizational Culture

Organizational culture carries inconsistent meaning across the literature (House et al. 2002). Gupta and George (2016) argue that organizational culture is a highly complex notion to understand and describe. Despite its heterogeneous nature, management scholars have posited that organizational culture may a source of competitive advantage (Barney, 1995). Along similar lines, scholars who have studied big data have acknowledged the importance of organizational culture (LaValle et al. 2014). Ross et al. (2013) argue that culture has the ability to inhibit (or enhance) an organization's ability to benefit from big data. Hence, it is understood that when management and employees at all levels do not believe in the potential of big data, the effort of the entire organization to extract potential benefits from big data will be in vain. Hence, following Ross et al. (2013) and Gupta and George (2016), we assume that organizational culture may have a significant influence on building BDPA capability.

2.7.2 Organizational Learning

In a dynamic environment, organizational learning is regarded as an important source of sustained competitive advantage (Teece et al. 1997). Grant (1991) argues that the sustained competitive advantage of organizations hinges on the intensity of organizational learning, which is a continuous process through which organizations explore, store, share, and apply knowledge. Nonaka et al. (2000) argue that knowledge does not wear out, however with the passage of time it may become outdated due to the emergence of new technologies. Hence, organizations need to continuously upgrade their existing knowledge over time to sustain competitive advantage in a dynamic environment. Those organizations that have the intensity for learning may remain competitive in the long run (Gupta and George, 2016). Thus, we argue that organizational learning is an important resource to build BDPA.

2.8 Visibility

Visibility is an important capability in managing supply chains (Barratt and Oke, 2007; Brandon-Jones et al., 2014). Visibility is related to the flow of information (Brandon-Jones et al., 2014) and allows supply chain partners to coordinate as they can see each other's inventory levels and replenishment quantities. This transparency in information flows can improve confidence and reduce interventions, which in turn improves decision making (Christopher and Lee, 2004). We suggest that visibility, similar to commercial supply chains, is also a driver for coordination in humanitarian relief supply chains.

2.9 Coordination

Balcik et al. (2010) define coordination in HRSCs as the relationship and interactions among different actors operating within the relief environment. They further argue that coordination in humanitarian relief supply chains may appear horizontal or vertical. Horizontal coordination refers to the extent to which an umbrella organization coordinates with their partners at the same level within the chain. NGOs prefer horizontal coordination (Balcik et al., 2010; Akhtar et al., 2012). Vertical coordination refers to the traditional hierarchical command-control structure of linking with partners in the chain. Government organizations and armed forces normally follow vertical coordination.

2.10 Swift trust

Meyerson et al. (1996) have coined the term "swift trust," which is essential for bringing temporary teams together with a clear purpose and common task for a finite period of time. Meyerson et al. (1996) argued the need for swift trust among members in a temporary group. The definition offered by Meyerson et al. (1996) is based on the arguments of Goodman and Goodman (1976), who identified the social constraints and resources found in temporary systems. Hence, in such situations, trust needs to be built urgently to improve the success of the humanitarian relief supply chain. Tatham and Kovacs (2010) argue that swift trust has a positive impact on building coordination among humanitarian supply chain actors.

3. Theoretical Framework and Hypotheses Development

The extant literature argues that the bundling of certain resources and capabilities may lead to competitive advantage. Here, we suggest that the interplay of tangible and intangible resources and BDPA (capability) may be useful for creating visibility (see Barratt and Oke, 2007; Brandon-Jones et al. 2014) and building coordination among actors in a humanitarian supply chain (Akhtar et al. 2012). Further, based on contingency theory, we offer that swift trust may influence the relationships between BDPA and visibility/coordination (see Sousa and Voss, 2008). We conceptualize our hierarchical model following Wetzels et al. (2009), representing the relationships between the indicators, sub-dimensions, and higher-order constructs (see Figure 1). Here basic resources, data, technology, tech skills, managerial skills, organizational culture and organizational learning are first-order reflective constructs which represent the previously described categories of organizational resources (see Grant, 1991). These resources were utilized to create the second-order reflective construct referred to as BDPA. BDPA leads to third-order reflective constructs as visibility and coordination following the RBV logic.

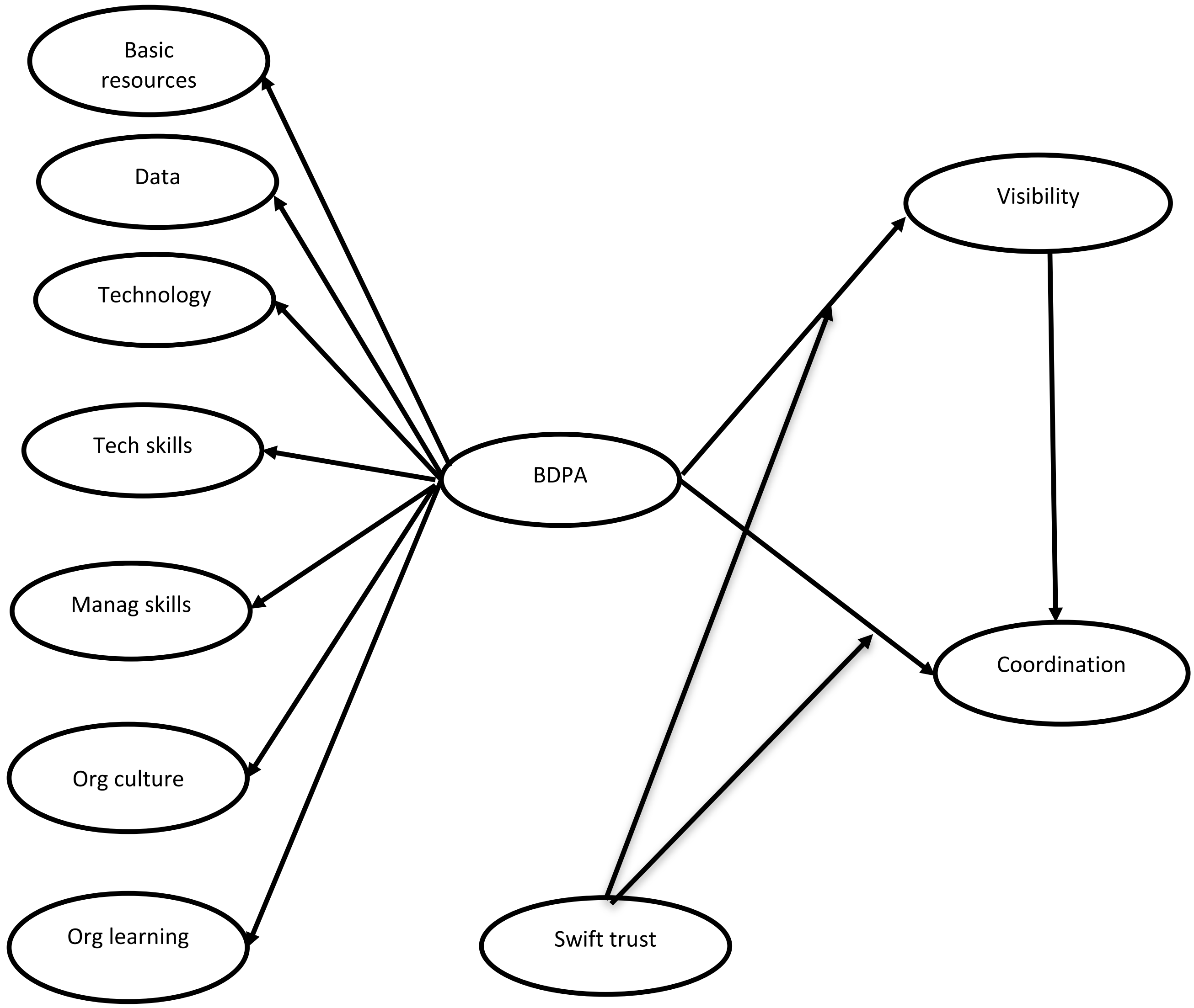

Figure 1: Conceptual Framework

3.1 BDPA and Visibility in Humanitarian Supply Chain

Blackhurst et al. (2005) suggest that supply chain visibility is a pressing concern. There is a consensus among scholars regarding visibility in the supply chain (see Barratt and Oke, 2007). However, despite its acceptance, organizations have often failed to address visibility. Inspired by Barratt and Oke's (2007) arguments, we argue that BDPA is an organizational capability (see

Gupta and George, 2016; Akter et al. 2016) that may have a significant influence on creating visibility in humanitarian supply chains. Papadopoulos et al. (2017) noted that BDPA can be a useful organizational capability to increase supply chain visibility and reduce behavioral uncertainty arising from information asymmetry (see Morgan and Hunt, 1994; Kwon and Suh, 2004), which can minimize opportunistic behavior among humanitarian supply chain actors. Behavioral uncertainty, the inability to predict who supply chain partners will be (here we refer to them as actors or agents; adapted from Joshi and Stump, 1999). Willamson (1985) argued that behavioral uncertainty can also be due to the lack of complete information about supply chain partners, which can impact supply chain performance. Lack of transparency among humanitarian actors can result in poor visibility (Balcik et al., 2010). Hence, following resource based view logic, we hypothesize the following:

H1: BDPA has a positive impact on visibility in humanitarian supply chain.

3.2 BDPA and Coordination among Humanitarian Actors

In the humanitarian supply chain literature, the importance of coordination among actors has attracted significant attention from scholars (see Balcik et al. 2010; Tatham and Kovacs, 2010; Akhtar et al. 2012; Kabra and Ramesh, 2015). Coordination among actors critically hinges on the quality of information sharing (see Balcik et al. 2010; Akhtar et al. 2012; Altay and Pal, 2014; Kabra and Ramesh, 2015). Altay and Pal (2014) further argued the need for information diffusion among agents to improve response in humanitarian supply chains. Information sharing among agents helps bridge cultural differences and creates transparency in the relationship. Akhtar et al. (2012) further argue that information sharing, trust, and commitment are important antecedents of coordination. Although there is significant literature focusing on the role of IT capabilities on improving coordination (see Li et al. 2002; McLaren et al. 2002; Ding et al. 2014), the impact of BDPA on coordination is still underdeveloped. However, recently, Prasad et al. (2016) argued using resource dependence theory (RDT), that use of big data may enhance humanitarian supply chain performance by providing information sharing and transparency. Hence, we posit that BDPA may have a positive influence on coordination among actors in humanitarian supply chains. Hence we hypothesize it as our second hypothesis (H2) as:

H2: BDPA has a positive impact on coordination among actors in humanitarian supply chain.

3.3 Visibility and Coordination

Behavioral uncertainty and opportunistic behavior are often cited as barriers to coordination in supply chains (Arshinder et al. 2008), and this lack of coordination often results in the failure of humanitarian supply chains to achieve their objectives (Balcik et al. 2010). Kabra and Ramesh (2015) argue that poor visibility in humanitarian supply chains often leads to information asymmetry, which results in poor coordination. Barratt and Oke (2007) noted in their study that supply chain visibility is a higher-order construct which requires interplay of strategic resources like quality information and information technology (i.e., resources provided by BDPA). Brandon-Jones et al. (2014) have further examined how visibility in supply chain reduces the risk due to environment uncertainties in the supply chain. However, though anecdotal evidence suggests that visibility in humanitarian supply chains may enhance coordination, rigorous empirical testing remains elusive. We draw our argument from the extant literature on supply chain visibility (Barratt and Oke, 2007; Brandon-Jones et al. 2014) and coordination (Arshinder et al. 2008; Balcik et al. 2010; Akhtar et al. 2012; Kabra and Ramesh, 2015; Tatham et al. 2017). These studies indicate that visibility in a humanitarian supply chain may have a positive influence on coordination among actors in the humanitarian supply chain. Moreover, BPDA may also have an indirect effect on coordination through visibility if it can provide information that improves visibility. Hence, we hypothesize as the following:

H3: High visibility in humanitarian supply chain will enhance coordination among actors in humanitarian supply chain, and as such, will mediate the relationship between BDPA and coordination.

3.4 Moderating role of swift trust

In case the of humanitarian supply chains, the notion of contingent conditions may help shape the behavior of the humanitarian actors, as humanitarian supply chains are often hastily formed (Tatham and Kovacs, 2010). Following Sousa and Voss (2008)'s arguments on the impact of contingent factors such as national context and culture, firm size, strategic context, and other organizational variables, we argue that swift trust may influence the relationships between BDPA and visibility/coordination. Sousa and Voss (2008) have noted that contingency research is often desired for the advancement of operations and supply chain research; however, to date, contingent perspectives on the RBV are underdeveloped in the literature (Tatham and Kovacs 2010). Hence, we propose swift trust may explain the role of BDPA in creating desired visibility and coordination in hastily formed humanitarian supply chains. Hence, we hypothesize it as:

H4: Swift trust positively moderates the relationship between BDPA and visibility in humanitarian supply chain: higher the swift trust the greater the beneficial effects of BDPA on visibility.

H5: Swift trust positively moderates the relationship between BDPA and coordination among actors in the humanitarian supply chain: higher the swift trust the greater the beneficial effects of BDPA on coordination among actors in the humanitarian supply chain.

H6: Swift-trust has positive moderated-mediation effect on the path joining BDPA-visibility-coordination;

4. Research Design

4.1 Survey Instrument

The items tapping the theoretical constructs were developed based on extensive review of the extant literature. Items were assessed on a five-point Likert scale with anchors ranging from strongly from strongly disagree (1) to strongly agree (5).

Before data collection, the instrument was pre-tested for content validity in two phases (Chen and Paulraj, 2004). In the first phase, we invited four experienced researchers to provide their critical inputs on our questionnaire for ambiguity, clarity, and appropriateness of the items used to operationalize each construct (DeVellis, 1991). We further asked these researchers to assess the extent to which the indicators sufficiently addressed the subject area (Dillman, 2007). Based on the inputs from these researchers, we have further modified the instrument to improve the clarity and the appropriateness of the measures purporting to tap the constructs (Chen and Paulraj, 2004).

In the second stage, we e-mailed to 20 managers from Asian Disaster Reduction Center (ADRC), National Institute of Disaster Management (NIDM) and China National Committee for Disaster Reduction (CNCDR). These managers were asked to review the questionnaire for structure, readability, ambiguity, and completeness. The final survey instrument incorporated the feedback received from these executives, which enhanced the clarity of the instruments. Hence, we can claim that a survey instrument was developed that was judged to exhibit high content validity.

4.2 Measures

The indicators used to measure the theoretical constructs are based on extensive literature review. The operationalization of the constructs discussed next (Table 1).

Table 1: Operationalization of Constructs

Construct and Derivation	**Types**	**Measures**
Basic resources adapted from Gupta and George (2016)	Reflective	1. We have allocated adequate funds for big data and predictive analytics. 2. We have enough time to achieve desired results from big data and predictive analytics.
Data adapted from Gupta and George (2016)	Reflective	1. We have access to large amounts of unstructured data for analysis. 2. We integrate data from multiple internal sources into a data warehouse. 3. We integrate external data with internal to facilitate high-value analysis of our business environment.
Technology adapted from Gupta and George (2016)	Reflective	1. We have explored or adopted parallel computing approaches to big data processing. 2. We have explored or adopted different data visualization tools. 3. We have explored or adopted cloud-based services for processing data and performing analytics. 4. We have explored or adopted open-source software for big data analytics. 5. We have explored or adopted new forms of databases such as Not Only SQL (NoSQL).

Technical skills adapted from Gupta and George (2016)	Reflective	1. We provide big data analytics training to our employees. 2. We hired employees that already have big data and analytics skill. 3. Our big data analytics staff have right skills to accomplish their jobs successfully. 4. Our big data staff has the suitable education to fulfill their jobs. 5. Our big data analytics staff have the suitable work experience to accomplish their jobs successfully. 6. Our big data analytics staff is well trained.
Managerial skills adapted from Gupta and George (2016)	Reflective	1. Our big data analytics managers understand and appreciate the needs of other members. 2. Our big data managers are able to work with other functional managers. 3. Our big data analytics managers are able to coordinate big-data-related activities in ways that support other partners. 4. Our big data analytics managers are able to anticipate future challenges. 5. Our big data analytics managers have a good sense of where to use big data. 6. Our big data analytics managers are able to interpret the analyses obtained using complex analyses and offer inputs which are useful for swift decision making.

Organizational culture adapted from Gupta and George (2016)	Reflective	1. We consider data as a valuable asset. 2. We base most of the decisions on data rather than instinct. 3. We are willing to override our intuition when data contradict our viewpoints. 4. We continuously assess our strategies and take corrective action in response to the insights obtained from data. 5. We continuously coach our people to make their decisions based on data.
Organizational learning adapted from Gupta and George (2016)	Reflective	1. We can search for new and relevant knowledge. 2. We can acquire new and relevant knowledge. 3. We can assimilate relevant knowledge. 4. We can apply relevant knowledge.
Swift trust adapted from Hung et al. (2004) and Tatham and Kovacs (2010)	Reflective	1. We have information about the actors involved. 2. Most people tell the truth about their knowledge. 3. There are clear rules for classification of processes and procedures. 4. We trust based on third party reference. 5. Category (i.e. gender, ethnicity, etc.).
Visibility adapted from Braunscheidel and Suresh (2007) and Brandon-Jones et al. (2014)	Reflective	1. Inventory levels are visible throughout the supply chain. 2. Demand levels are visible throughout the supply chain.
Coordination Adapted from Balcik et al. (2010); Akhtar et al. (2012) and Basnet (2013)	Reflective	1. We consult other members before making decisions. 2. We understand the pressures and concerns of each other 3. We synchronize our activities with each other.

We also included three control variables that may affect the findings. Relationship duration, defined as the age of association between two partners, can impact swift trust and degree of coordination because the long-term association often leads to high trust and better coordination (Tatham and Kovacs, 2010). Following Moshtari (2016), we control for interdependency perception. Finally, we include the time since the adoption of BDPA as a control variable for the reason that adoption is a time-sensitive process and any level of misalignments that might have existed initially may have been resolved by users and managers to various degrees at the time the survey was conducted. Following Fichmann (2001), this variable accounts the accumulated organizational learning and experience that facilitates proper exploitation of the capability to improve the performance.

4.3 Data Collection

We started data collection by sending out an invitation letter to 890 potential respondents via e-mail, followed by three e-mail reminders. We gathered list of the NGOs using Asian Disaster Reduction Center (ADRC) database. We have assured our respondents that in all circumstance we will maintain strict anonymity and their information will not be shared with any other agencies. We have mentioned in the invitation letter that to take part, a respondent's organization must be an international NGO and are partner with at least one other international NGO. After identifying respondents as a key informant, we qualified them by analyzing how knowledgeable they are themselves about their own organization and their level of coordination with their organization and their partners (Moshtari, 2016). To avoid the problems of social desirability (Podsakoff et al. 2003), which is one of the common sources of common method bias (CMB), we requested that the participants base their responses on one international NGO partnership with which they have had recent (within the past year) collaboration. Finally, we have obtained 238 usable questionnaires which were sent via e-mail. We discarded 33 filled questionnaires as they failed to meet the characteristics of target respondents (i.e. respondents were not knowledgeable about their coordination role with their partners or due to missing data). We finally had 205 responses, an effective response rate of 23.03 %. This response rate is also similar or better than to previous studies (see 13% response rate in Moshtari, 2016 or 6% response rate in Cao and Zhang (2011).

All participants are key informants who hold managerial positions in their organizations (head of the organizations/director, 14.63%; head of analytics/ MIS, 12.20%; logistics manager 39.02% and procurement manager, 34.15%).

30.24% of the respondents have worked for less than two years in the same organization, 24.39 % of the respondents who have worked for two years and more but less than five years in the same organization. 43.90 % of the respondents who have worked for five years and more but less than ten years in the same organization. 1.46% of the respondents who have worked for more than ten years in the same organization.

Regarding organization's size, 9.76 % of the organizations have less than 25 employees, 21.95% of the organizations have 25 or more employees but less than 50 employees in an organization. 36. 59% of the organizations have 50 or more employees but less than 100 employees in an organization. 31.71% of the organizations have 100 or more employees in an organization (see Appendix 1).

4.4 Non-Response Bias

Armstrong and Overton (1977) argue that in case when data is gathered, there is a possibility that the response of the early respondents may differ from the late respondents. Further, Chen and Paulraj (2004) argue that in case of statistical surveys the non-response bias test is one of the prerequisite requirements. Hence, before the data can be used for further statistical analyses, it is always advisable to conduct non-response bias test using wave analysis. In this approach depending upon data distribution either chi-square test or t-test is performed on early responses and late responses to check whether significant statistical difference exists. In recent years, there are increasing trends among operations management research community to use wave analysis to check non-response bias (see, Blome et al.2013; Dubey and Gunasekaran, 2015; Lee et al. 2016). In our case, we have split the collected data into two equal halves as suggested by Chen and Paulraj (2004) depending on the dates they were received. We assessed non-response bias test on two halves using t-tests. We have found no significant differences ($p>0.05$). Hence, we concluded that non-response bias may not be a serious concern.

5. Data Analyses and Results

Before undertaking statistical analyses, we have performed following prerequisite assumption tests which include constant variance, existence of outliers, and normality (see, Chen and Paulraj, 2004; Blome et al.2013; Dubey and Gunasekaran, 2015). We used plots of residuals by predicted values, rankits plot of residuals, and statistics of skewness and kurtosis (Cohen et al. 2003). In our case, we found that maximum absolute values of skewness and kurtosis of the indicators in the remaining dataset were found to be 1.67 and 2.37, respectively. These values were much below than the reported limits in the past research (skewness <2, kurtosis <7) (Curran et al. 1996; Kim and Malhotra, 2005; Blome et al. 2013; Dubey and Gunasekaran, 2015).

5.1 Measurement Model

We note that all the reliability coefficients are above 0.70, the standardized factor loadings of each item is above 0.5, the composite reliability (SCR) are above 0.5 and each construct average variance extracted (AVE) is above 0.5 (see Table 2), indicating that the measurements are consistent, latent construct account for at least 50 percent of the variance in the items. Hence it is evident that our constructs of the theoretical framework (see Figure 1) demonstrates convergent validity. The Table 3 shows that the square root of the AVE in the leading diagonal is greater than all the entries in the given row and column (i.e. above correlation coefficient values). The results in Table 3 further suggest adequate discriminant validity.

Table 2: Loadings of the Indicator Variables (Composite Reliability) and Average Variance Extracted (AVE)

Indicators	Factor Loadings	Variance	Error	SCR	AVE
BR1	0.75	0.56	0.44	0.72	0.56
BR2	0.75	0.56	0.44		
DAT1	0.77	0.60	0.40	0.75	0.60
DAT3	0.77	0.60	0.40		
TECH1	0.89	0.80	0.20	0.94	0.77
TECH2	0.94	0.89	0.11		
TECH3	0.91	0.83	0.17		
TECH4	0.90	0.81	0.19		
TECH5	0.74	0.54	0.46		
TS1	0.78	0.61	0.39	0.92	0.65
TS2	0.83	0.69	0.31		
TS3	0.83	0.70	0.30		
TS4	0.81	0.66	0.34		

TS5	0.81	0.65	0.35		
TS6	0.79	0.63	0.37		
MS1	0.87	0.76	0.24	0.95	0.75
MS2	0.89	0.79	0.21		
MS3	0.92	0.84	0.16		
MS4	0.90	0.81	0.19		
MS5	0.90	0.81	0.19		
MS6	0.70	0.49	0.51		
OC3	0.98	0.95	0.05	.983	0.95
OC4	0.97	0.95	0.05		
OC5	0.97	0.95	0.05		
OL2	0.68	0.46	0.54	.781	0.54
OL3	0.78	0.60	0.40		
OL4	0.75	0.57	0.43		
ST2	0.94	0.87	0.13	.933	0.78
ST3	0.88	0.78	0.22		
ST4	0.92	0.85	0.15		
ST5	0.78	0.61	0.39		
VISIB1	0.97	0.94	0.06	.970	0.94
VISIB2	0.97	0.94	0.06		
CO1	0.65	0.43	0.57	.887	0.73
CO2	0.94	0.87	0.13		
CO3	0.94	0.88	0.12		

Table 3: Correlations among Major Constructs

	BR	DAT	TECH	TS	MS	OC	OL	ST	VISB	CO
BR	**0.75**									
DAT	0.39	**0.78**								
TECH	0.26	0.63	**0.88**							
TS	0.23	0.00	-0.03	**0.81**						
MS	0.60	0.61	0.46	0.11	**0.87**					
OC	0.09	0.15	0.17	0.05	0.24	**0.98**				
OL	-0.22	-0.17	-0.18	-0.09	-0.28	-0.04	**0.74**			
ST	-0.05	0.05	0.02	-0.02	-0.04	0.12	0.30	**0.88**		
VISB	-0.06	-0.01	0.00	0.05	-0.04	0.13	0.15	0.03	**0.97**	
CO	0.16	0.23	0.25	-0.02	0.27	0.07	-0.39	-0.08	0.06	**0.85**

5.2 Common Method Bias

Podsakoff et al. (2003) argue that in the case of self-reported data, there is a possibility for CMB from multiple sources such as consistency motif and social desirability. Since we have no interference in the process of responding to the questionnaire, hence we had no control on self-reported data. In such case, we performed statistical analyses to assess the severity of CMB. Harman's one-factor test as suggested by Podsakoff and Organ (1986) was conducted on ten constructs of our model (Figure 1). Following Podsakoff and Organ (1986), we performed an exploratory factor analysis and reduced to a single factor by fixing the number of factors to be extracted equal to 1. The maximum variance explained by the single extracted factor is 41.93 %. However, in recent years operations management scholars have expressed their serious concerns on CMB (see Guide and Ketokivi, 2015). Since we have used cross-sectional data using a survey instrument, the CMB may be a concern. It is worth noting that the impact of CMB may be minimized by tightening our research design. Since we have collected data from multiple respondents from the same organization (see data collection section), we may argue that CMB may not be a major issue.

5.3 Causality Test

Following Guide and Ketokivi (2015)'s arguments that statistical analyses based on cross-sectional survey data or non-experimental data need to perform endogeneity testing before undertaking hypotheses testing, hypotheses we tested for endogeneity of the exogenous variable. In our theoretical model (see Figure 2), BDPA is conceptualized as an exogenous variable to the visibility and coordination among actors in humanitarian supply chain, but not the other way round using RBV logic. Thus, endogeneity is unlikely to be a concern in this context. We also examined whether endogeneity was an issue by conducting Durbin-We-Hausman test (Davidson and Mackinnon, 1993). We first regressed BDPA on visibility and coordination, and then we have used the residual of this regression as an additional independent variable in our hypothesized equations. The parameter estimate for the residual was not significant, indicating that BDPA was not endogenous in our setting, consistent with our conceptualization.

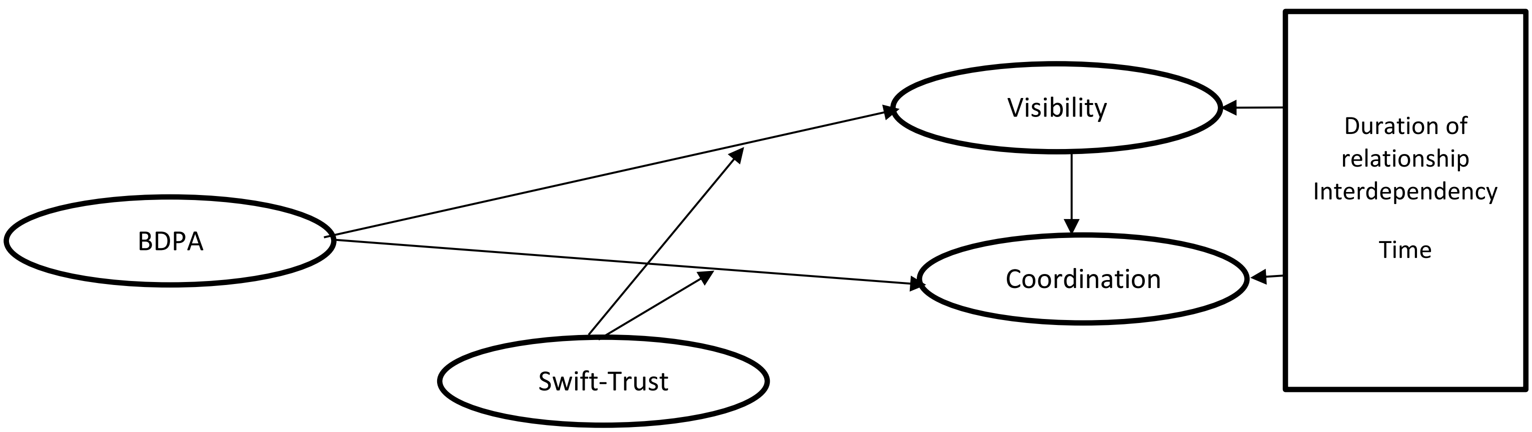

Figure 2: Theoretical Model

5.4 Hypothesis Testing

We have tested our research hypotheses with multiple hierarchical regression analysis, with hierarchical moderated regression tests applied as necessary. All variables are mean-centered to reduce the risk of multicollinearity of the interaction terms. The multicollinearity is measured by calculating variance inflation factors (VIF) for each regression coefficient. In our case, the VIF values range from 1.05 to 1.775, significantly below the recommended threshold of 10 (Hair et al. 2006). Table 4 provides the results of hierarchical multiple regression and hierarchical moderated regression analyses.

The Table 4 examines hypothesized linkages between BDPA and visibility/coordination and the interaction effect of swift trust on the path connecting BDPA and visibility/coordination as specified in H1-H5. Addressing H1 first, we observe support (Table 4) for the impact of BDPA on visibility in the supply chain (β=1.334; p=0.000). This finding is consistent with the anecdotal and conceptual evidence (see Lewis, 2014). The control variables: duration of relationship, interdependency and time has no significant effect in this model. From this finding, we interpret that duration of relationship, interdependency and time have little role to play in the influence of

BDPA on visibility in humanitarian supply chain. This result runs contrary to many findings as we have drawn our second hypothesis by the commercial supply chain literature where the duration of relationship and interdependency have significant effect. However, the humanitarian supply chains are often hastily formed (Tatham and Kovacs, 2010) and the relationship among partners are often shorter in comparison to those of commercial supply chains. This result brings some useful insights which may help to shape the growing humanitarian supply chain literature. Addressing H2, we find support (Table 4) for the positive impact of BDPA on coordination among actors in the humanitarian supply chain (β=1.372; p=0.000). This finding is consistent with prior literature which argues that IT capabilities have a positive influence on coordination level (Li et al. 2002; McLaren et al. 2002; Ding et al. 2014). The control variables: duration of relationship, interdependence and time have no significant effect in this model. From these findings, we may conclude that the humanitarian supply chains are far more complex than commercial supply chains (Balcik et al. 2010; Kovacs and Spens, 2011); hence the humanitarian supply chain needs different angle.

Next addressing H3, we find support (Table 4) that visibility in the humanitarian supply chain is a strong predictor of coordination (β=0.658; p=0.000) among the actors in the humanitarian supply chain. This is consistent with prior conceptual findings where visibility in the humanitarian supply chain has significant influence on coordination among actors in humanitarian supply chain (Akhtar et al. 2012; Kabra and Ramesh, 2015).

H4 and H5 were tested using hierarchical multiple moderated regression analysis (Table 5 and Table 6). In this case, we have performed three steps process. In the first step, we examined the direct impact of the control variables on visibility and coordination. We observe that none of these control variables have a significant influence on visibility and coordination. In the second step, we examined the direct effects of the BDPA and the moderator variable (swift-rust) on visibility and coordination (Table 5 and Table 6). The model indicates that the swift trust has a significant direct effect on visibility (β=0.752; p=0.000) and coordination (β=1.662; p=0.000). The result suggests that if humanitarian organizations can build swift trust among the actors involved in disaster relief supply chain, these organizations can create high visibility in supply chain and the coordination level among the actors in the supply chain will be higher. We can claim that our results make notable contribution to the swift trust variable and its impact on visibility in humanitarian supply chain and coordination among actors in humanitarian supply chain as conceptualized in context to humanitarian supply chain network which are often hastily formed, hence the rapid formation of trust among actors may have significant influence on coordination and collaboration which are important antecedents of humanitarian supply chain performance (Tatham and Kovacs, 2010). In the third step, we included the interaction effect in the model. However, we observed that swift trust have no moderation effect on the path joining BDPA and visibility (β=-0.017; p=0.896) and BDPA and coordination (β=-0.194; p=0.076). We interpret that swift trust does not moderate the relationship, although post-hoc analysis revealed that it has a high direct effect on visibility and coordination.

Table 4: Regression Results for Visibility and Coordination

Variables	DV= Visibility		DV= Coordination	
Controls	Beta	p-value	Beta	p-value
Duration of relationship	0.017	0.668	0.023	0.431
Interdependency	-0.005	0.872	-0.023	0.318
Time	0.004	0.915	0.018	0.547
Main effects				
BDPA	1.334	0.000	1.372	0.000
Visibility			0.658	0.000
Model summary				
R^2	0.600		0.752	
Adj R^2	0.592		0.747	
Model F	28.8		4.3	

Table 5: Hierarchical Moderated Regression Results for Visibility

Variables	Control Model		Main Effects Model		Full Model	
Controls	Beta	p-value	Beta	p-value	Beta	p-value
Duration of relationship	0.047	0.444	0.008	0.799	0.047	0.444
Interdependency	-0.049	0.319	-0.023	0.380	-0.049	0.319
Time	0.116	0.060	0.019	0.570	0.116	0.060

Main effects						
BDPA			0.724	0.000	0.792	0.000
Swift trust			0.752	0.000	0.826	0.000
Interaction effects						
BDPA * Swift trust					-0.017	0.896
Model summary						
R^2	0.021		0.725		0.725	
Adj R^2	0.007		0.718		0.717	
Model F			105.023		87.09	
ΔR^2					-17.93	

Table 6: Hierarchical Moderated Regression Results for Coordination

Variables	Control Model		Main Effects Model		Full Model	
Controls	Beta	p-value	Beta	p-value	Beta	p-value
Duration of relationship	0.054	0.342	0.027	0.319	0.054	0.342
Interdependency	-0.068	0.132	-0.014	0.503	-0.068	0.132
Time	0.132	0.020	0.011	0.613	0.132	0.020
Main effects						
BDPA			0.358	0.000	2.419	0.000
Swift trust			1.662	0.000	0.470	0.000
Interaction effects						
BDPA * Swift trust					-0.194	0.076
Model summary						
R^2	0.035		0.785		0.789	
Adj R^2	0.020		0.780		0.782	
Model F			145.423		123.044	
ΔR^2					0.039	

Finally, addressing H6 which examine whether ST has moderated mediation effect on the path joining BDPA-visibility-coordination. Muller et al. (2005) argues that in statistics, moderation and mediation may occur together in the same model. The moderated mediation is also known as conditional indirect effects occurs when the effect of the independent variable (in our case it is BDPA) on outcome variable (coordination) via visibility as a mediating variable differs depending on the levels of swift-trust as a moderating variable. Specifically, either the effect of visibility on coordination depends on the level of swift trust.

Following Langfred (2004) and Muller et al. (2005) arguments on moderated mediation analysis on proposed models (i.e. *Model 1*, *Model 2 & Model 3*), we have performed hierarchical moderated mediation regression analyses (see Table 7). The interaction effect between swift trust and BDPA (β=-0.188; p=0.359)/ visibility (β=-0.001; p=0.990) are insignificant. Hence, H6 is not supported. Since we have observed that swift-trust has mediation effect, thus we can argue that swift-trust is not a condition for achieving coordination but an important construct which may have mediating effect between BDPA and coordination. This result makes an interesting contribution to the existing literature that swift-trust which is highly desirable for efficient and effective coordination among actors in humanitarian supply chains (Tatham and Kovacs, 2010), the BDPA plays a significant role in building swift-trust.

Table 7: Hierarchical Moderated Mediation Regression Results for Coordination

Steps and variables	**Model 1 (mediation)**		**Model 2 (moderations)**		**Model 3 (mediated moderation)**	
Controls	**β**	**p-value**	**β**	**p-value**	**β**	**p-value**
Duration of relationship	0.025	0.55			0.054	0.34
Interdependency	-0.038	0.259			-0.068	0.132
Time	0.062	0.148			0.132	0.020
Main effects						
BDPA	1.370	0.000			2.238	0.000
Visibility	0.608	0.000	0.852	0.000	0.224	0.000
Swift-trust			-0.075	0.856	0.286	0.000
Interaction effects						
ST*Visibility			-0.034	0.756	-0.001	0.990
ST*BDPA					-0.188	0.359
Model summary						
R^2	0.459		0.467		0.804	
F	42.43		28.97		100.422	

6. Discussion

6.1 Theoretical Contributions

Following the logic of CRBV, we have conceptualized that how BDPA as an organizational capability may be used for improving visibility in humanitarian supply chain and coordination among actors under the contingent effect of swift trust. In the supply chain literature, visibility in supply chain is regarded as higher-order construct (i.e. capability) (see Barratt and Oke, 2007; Brandon-Jones et al. 2014). However, in recent studies, Akter et al. (2016) and Gupta and George (2016) argue that BDPA is an organizational capability based on RBV logic. Hence, by extending the arguments of Akter et al. (2016) and Gupta and George (2016) to examine how BDPA as a capability can improve visibility in humanitarian supply chain and coordination among actors in humanitarian supply chain under contingent effect of swift trust, we offer two important contributions to the existing literature. First, this paper demonstrates that visibility and coordination are two discrete properties of humanitarian supply chains which can be significantly improved using BDPA. This is one of the first studies to empirically examine the impact of BDPA on visibility and coordination in context to humanitarian supply chain. The existing literature is full of anecdotal evidence and conceptual arguments, the empirical research involving rigorous testing is scant. Second, this paper provides an empirical evidence that swift trust acts as an antecedent of visibility and coordination in humanitarian supply chain context. In prior research, Tatham and Kovacs (2010) argue the role of swift trust in hastily formed supply chains. However, the empirical test of the role of swift trust is scant. Further, we found that BDPA has a significant influence on building swift trust among actors in humanitarian supply chain. Hence, our results on swift trust offer interesting insights which can further expand the current understanding of humanitarian supply chains.

6.2 Managerial Implications

This study offers several useful implications for managers working in humanitarian organizations (i.e. NGOs or government agencies) who want to exploit the BDPA which is currently one of the most important forces which may shape future supply chains (Waller and

Fawcett, 2013; Fawcett and Waller, 2014). However, the understanding of BDPA in context to humanitarian supply chain is still underdeveloped. Hence, our study makes three important contributions from managerial perspective. First, what are the important organizational resources that can be utilized to create BDPA which is acknowledged by the scholars as an important organizational capability. Second, how interplay of BDPA and swift trust can help to improve visibility in humanitarian supply chains and improve coordination among actors in humanitarian supply chain. Earlier, the BDPA understanding was limited to tweet analysis or identifying potential sources of the risk. Thus, the use of BDPA in improving visibility in building effective coordination among humanitarian actors can advance this stream of research. Finally, the role of swift trust and BDPA may further enhance the usefulness of BDPA in the context of humanitarian supply chains which are far more complex than commercial chains due to high degree of uncertainties, different language, different culture and complex organizational structure. We hope our results will further motivate managers involved in disaster relief operations to exploit the BDPA to improve the humanitarian supply chain performance in the big data environment.

7. Conclusions, *Limitations and Further Research Directions*

Drawing broadly on CRBV, we have conceptualized our theoretical model grounded in existing literature drawn from two diverse areas: information systems management and humanitarian supply chain management. Our theoretical framework reconciles the independent contributions of two well-established streams in the literature: BDPA as an organizational capability (Akter et al. 2016; Gupta and George, 2016) and humanitarian supply chain (Balcik et al. 2010; Tatham and Kovacs, 2010; Akhtar et al. 2010). We attempt to explicate how swift trust plays a significant role in improving visibility and coordination among actors in humanitarian supply chains. Analyses are based on 205 survey responses gathered from international NGOs who are engaged in collaborative disaster relief operations across the globe. The research makes notable contribution to the growing BDPA literature and swift trust by empirically testing the framework. It confirms that BDPA has a significant influence on swift trust and further interplay of BDPA and swift trust improves visibility and coordination. This extends our understanding as the existing literature offers anecdotal and conceptual evidence. The empirical findings illuminate the role of BDPA on improving swift trust, visibility and coordination, which extends our knowledge in humanitarian supply chains which are far more complex than commercial supply chains.

We have outlined the limitations and potential areas for future research. As we have used cross-sectional data to test our research hypotheses, we cannot ignore the presence of CMB and endogeneity. Although we have taken precautions in our study by following Guide and Ketokivi (2015)'s suggestions, use of longitudinal data may reduce CMB and endogeneity related issues. In addition, future research could examine other resources and capabilities which might enhance visibility or coordination or inter-organizational capabilities. Future studies may consider country culture or supply base complexity as contingent variables in our existing model. This knowledge may help us to understand under what context visibility or coordination may improve. Finally, we accept the limitation of a survey-based research. Hence to expand the scope, we recommend use of multi-research methods. Altay and Pal (2014) have used agent-based simulation (ABS) to study the interplay of resources to enhance the coordination. Hence, we suggest using ABS to advance understanding on the complex nature of swift trust and the interplay of resources and capabilities to enhance swift trust and coordination in context to humanitarian supply chains.

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Appendix 1: Demographic Profiles of the Respondents

1.Designation

	N	%
Head of the country	30	14.63
Head of Analytics/ Management Information System	25	12.20
Logistics Manager	80	39.02
Procurement Manager	70	34.15

2. Number of Employees in the Organization

	N	%
Number of Employees		
Less than 25	20	9.76
Greater than 25 but less than or equal to 50	45	21.95
More than 50 but less than 100	75	36.59
Greater or equal to 100	65	31.71

3. Length of affiliation with the current organization

	N	%
Worked less than two years in the same organization	62	30.24
Worked for more than two years but less than five years in the same organization	50	24.39

Worked for five years and more but less than 10 years in the same organization	90	43.90
Worked for more than ten years in the same organization	3	1.46

Appendix 2: Rotated Matrix

	1	2	3	4	5	6	7	8	9	10	11
BR1	.751										
BR2	.751										
DAT1		.774									
DAT2		***									
DAT3		.774									
TECH1			.892								
TECH2			.944								
TECH3			.911								
TECH4			.897								
TECH5			.736								
TECH_SKL1				.778							
TECH_SKL2				.828							
TECH_SKL3				.834							
TECH_SKL4				.811							
TECH_SKL5				.807							
TECH_SKL6				.794							
MS1					.871						
MS2					.889						

MS3					.916						
MS4					.902						
MS5					.900						
MS6					.700						
OC1						***					
OC2						***					
OC3						.976					
OC4						.974					
OC5						.973					
OL1							***				
OL2							.679				
OL3							.776				
OL4							.755				
ST1								***			
ST2								.935			
ST3								.884			
ST4								.921			
ST5								.782			
VISIB1									.970		
VISIB2									.970		
CO1											.653
CO2											.935
CO3											.939

Appendix 3: Harman's Single Factor Test

Component		Initial Eigenvalues			Extraction Sums of Squared Loadings		
		Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
dimension0	1	17.192	41.932	41.932	17.192	41.932	41.932
	2	6.616	16.136	58.068			
	3	3.435	8.377	66.445			
	4	2.590	6.317	72.762			
	5	1.984	4.840	77.602			
	6	1.548	3.775	81.377			

	7	1.209	2.949	84.326			
	8	1.014	2.472	86.799			
	9	.786	1.917	88.716			
	10	.629	1.534	90.250			
	11	.554	1.351	91.600			
	12	.519	1.267	92.867			
	13	.398	.971	93.838			
	14	.372	.907	94.746			
	15	.350	.854	95.600			
	16	.301	.735	96.335			
	17	.253	.617	96.953			
	18	.237	.578	97.530			
	19	.189	.460	97.990			
	20	.173	.421	98.411			
	21	.134	.327	98.738			
	22	.129	.314	99.052			
	23	.095	.231	99.284			
	24	.085	.207	99.490			
	25	.074	.181	99.671			
	26	.067	.164	99.835			
	27	.028	.068	99.903			
	28	.024	.059	99.962			
	29	.016	.038	100.000			
	30	1.378E-15	3.362E-15	100.000			
	31	3.585E-16	8.744E-16	100.000			
	32	1.776E-16	4.331E-16	100.000			
	33	1.074E-16	2.619E-16	100.000			
	34	5.361E-17	1.308E-16	100.000			
	35	7.357E-18	1.794E-17	100.000			
	36	1.681E-18	4.099E-18	100.000			
	37	-1.857E-17	-4.528E-17	100.000			
	38	-3.445E-17	-8.403E-17	100.000			
	39	-7.721E-17	-1.883E-16	100.000			
	40	-8.426E-17	-2.055E-16	100.000			

	41	-1.443E-16	-3.521E-16	100.000			